DYANAMIC STABILITY ASSESSMENT OF POWER SYSTEM USING MULTILAYER FEEDFORWARD NEURAL NETWORKS WITH REDUCED FEATURE SELECTION

LỰA CHỌN GIẢM BIẾN ĐẶC TRƯNG TRONG ĐÁNH GIÁ ỔN ĐỊNH ĐỘNG HỆ THỐNG ĐIỆN SỬ DỤNG MẠNG NEURAL TRUYỀN THẲNG NHIỀU LỚP

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TÓM TẮT

Bài báo giới thiệu ứng dụng mạng neural truyền thẳng nhiều lớp trong đánh giá ổn định động hệ thống điện với kỹ thuật giảm biến đặc trưng. Từ kết quả mô phỏng theo miền thời gian, trạng thái ổn định động của hệ thống điện được xác định dựa trên độ lệch góc rotor tương đối của các máy phát điện. Nghiên cứu minh họa đã được thực thi trên sơ đồ IEEE 9-bus tại các mức tải khác nhau với sự cố ngắn mạch ba pha tại các bus và dọc theo các đường dây truyền tải. Dữ liệu thu thập từ kết quả mô phỏng được cấp cho đầu vào mạng neural. Số lượng biến đặc trưng đầu vào cấp cho mạng neural được giảm dựa trên hàm phân biệt Fisher và phân tích tương quan. Kết quả đánh giá ổn định hệ thống điện IEEE 9-bus sử dụng mạng neural cho thấy độ chính xác nhận dạng cao, tỉ lệ sai sót thấp.

Từ khóa: *đánh giá ổn định hệ thống điện, mạng neural, lựa chọn biến đặc trưng.*

ABSTRACT

This paper presents an application of Multilayer Feed-forward Neural Networks (MLFN) for Dynamic Stability Assessment (DSA) with feature reduction techniques. Dynamic stability of the power system is first determined based on the generator relative rotor angles obtained from time domain simulations. Simulations were carried out on the IEEE 9-bus test system considering three phase faults on at different loading conditions. The data collected from the time domain simulations are then used as inputs to the MLFN. Reduced feature inputs based on Fisher Discrimination (FD) and correlation analysis (CA). MLFN results show that the stability condition of the power system can be predicted with high accuracy and less misclassification rate.

Keywords: *dynamic stability assessment, neural networks, feature/variable selection.*

I. INTRODUCTION

Modern power systems are forced to operate under highly stressed operating conditions closer to their stability limits. Perturbations could endanger system stability and may lead to power system collapse. The stability of power systems deals with the character of the electro-mechanical oscillations of synchronous generators created by a disturbance. Dynamic stability refers to the ability of synchronous machines of an interconnected power system to remain synchronism after being subjected to a large disturbance [1]. Large disturbance rotor angle stability is concerned with the ability of the power system to maintain synchronism when subjected to a severe disturbance, such as a short circuit on a transmission line or bus. Due to the complexity of the power system, traditional methods to power system analysis take so much time and cause delays indecision making. In recent years artificial neural networks (ANN) have been proposed as an alternative method for solving certain difficult power system problems where the conventional techniques have not achieved the desired speed and efficiency [4]. By learning from a dynamic stability database, the nonlinear relationship between the power system operating parameters and the corresponding stability states can be extracted and reformulated in an ANN [2]. It is important that ANN is well characterized, so the best input features must be selected. These features increase with the size of the power system, so the need to find solutions to extract feature reduction, data clustering enable ANN to handle data quickly but improve accuracy. This helps solve the problem of fast stability assessment of power systems and early warning unstable case.

In the remainder of this paper, Section 2 presents Mathematical model of multi-machine power system. Section 3 is about Multilayer Feed-forward Neural Network (MLFN). Feature selection technique is explained in Section 4. Performance evaluation of MLFN for dynamic stability assessment and discussion about the obtained results are presented in Section 5. Conclusion is drawn in Section 6and the future research is also this section.

II. MATHEMATICAL MODEL OF MULTIMACHINE POWER SYSTEM

The dynamic behavior of a generator power system can be described by the following differential equations [1]:

$$M_i \frac{d^2\delta_i}{dt^2} = P_{mi} - P_{ei} \quad (1)$$

It is known that,

$$\frac{d\delta_i}{dt} = \varpi_i \quad (2)$$

By substituting (2) in (1), therefore (1) becomes:

$$M_i \frac{d\varpi_i}{dt} = P_{mi} - P_{ei} \quad (3)$$

Where: δ_i: rotor angle of machine i

ω_i: rotor speed of machine i

P_{mi}: mechanical power of machine i

P_{ei}: electrical power of machine i

M_i: moment of inertia of machine i

A time domain simulation program can solve these equations through step-by-step integration by producing time response of all state variables.

III. MULTILAYER FEEDFORWARD NEURAL NETWORKS [6]

MLFN are the most popular neural networks. MLFN consist of at least three layers: an input layer, a hidden layer and an output layer. In the proposed feed forward neural network, input vector is fed to the input layer from the input data, the weight and the biases are adjusted using the activation function. The training is done by feeding the training data as well as the target data. This network is normally train by back propagation algorithm. There are a number of variations on the basic algorithm that is used for standard optimization techniques, such as Gradient Descent, Gradient Descent with Momentum, Bayesian Regularization, quasi-Newton, Levenberg-Marquardt…The fastest training function is generally Levenberg-Marquardt. The quasi-Newton method is also quite fast. Both of these methods tend to be less efficient for large networks. Also, Levenberg-Marquardt performs better on function fitting (nonlinear regression) problems than on pattern recognition problems. When training large networks, and when training pattern recognition networks, Scaled Conjugate Gradient and Resilient Back-propagation are good choices. Their memory requirements are relatively small, and yet they are much faster than standard gradient descent algorithms. The algorithm progresses iteratively through a number of epochs. On each epoch the training cases are each submitted to the network and target and number of outputs compared and the errors calculated. The network is also updated and the process continues. Training stops each time the training time elapses or when the number of epoch is reached. Also, whenever the error reaches acceptable level, the training stops. The whole exercise can be done as many times as possible until the desire target is reached. There are two different ways in which training can be implemented: incremental mode and batch mode. In incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In batch mode, all the inputs in the training set are applied to the network before the weights are updated.

In this paper, MATLAB toolbox is used as a computing tool to implement the MLFN. MLFN is composed of input layer, one hidden layer and one output layer. The hidden layer consists of five neurons with activation function tansig. Output layer consists of a single neuron with activation function purelin. Levenberg-Marquardt optimization based for weight and bias updating algorithm is selected.

IV. FEATURE SELECTION TECHNIQUES

Feature selection is a process used to identify a combination of features which contain valuable information that efficiently characterizes and represents all system data and generates input/output pattern of the ANN.

Among all the features originally selected, some features may be redundant and do not contribute to the discrimination of the features. In ANN based DSA models, feature selection is always needed to eliminate redundant features by which the size of training data can be significantly reduced and therefore training speed can be accelerated and the classification accuracy can also be enhanced.

This section gives a brief outline of reduced feature inputs based on Fisher Discrimination (FD) and Correlation Analysis (CA).

- *Fisher discrimination* [2]]-[3]: The Fisher approach is based on the projection of D-dimensional data onto a line. The hope is that such projections onto a line will be well separated by class. Given a set of n D-dimensional training samples $x_1, x_2, ..., x_n$ with n_1 samples in class C_1 and n_2 samples in class C_2, the task is to find the linear mapping, $y=w^Tx$, that maximizes:

$$F(w) = \frac{(m_1 - m_2)^2}{\sigma_1^2 + \sigma_2^2} \tag{4}$$

Where: m_i is the mean of class C_i and σ^2_i is the variance of C_i.

Features with greater F have more discriminating power, and are chosen as relevant attributes.

-*Correlation Analysis* [8]:

Correlation analysis (CA) is a statistical method of indicating the strength and direction of a linear relationship between two random variables. The correlation coefficient matrix represents the normalized measure of the strength of linear relationship between variables. Correlation coefficient (CC) between two random variables x and y is defined as:

$$CC = \frac{\operatorname{cov}(x, y)}{\sqrt{\operatorname{var}(x)\operatorname{var}(y)}} \tag{5}$$

Where: var( ) denotes the variance of a variable and cov( ) denotes the covariance between two variables.

In this paper if the features are 95% or more correlated with each other, one of them is retained and the other is discarded from the total features.

V. PERFORMANCE EVALUATION OF MLFN FOR DYNAMIC STABILITY ASSESSMENT

1. Studied System Description

IEEE 9-bus considered for dynamic stability assessment using the proposed method is given in Figure.1. The IEEE 9-bus test system consists of 3 generators, 6 lines, 3 transformers and 3 loads. In this paper, test systems were implemented using the Power World software for IEEE 9-bus system. Input/output pattern is generated by applying three phase fault at different locations on the line. The dynamic performance of the system during fault is based on observation of relative rotor angles of generators. The system state is

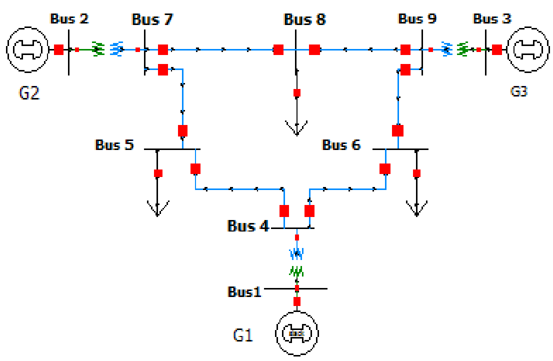

Figure.1 IEEE 9-bus system.

as Stable if the relative rotor angle of any generator δ_i with respect to generator δ_j does not exceed 180^0 after fault clearing, under a specified transient disturbance. On the contrary, if the relative rotor angle exceeds 180^0, the system state is classified as Unstable. A binary label is used to denote the dynamic stability status according to the following rules [5],[7]-[8]:

$$\begin{array}{ll} \text{if } \delta_{ij} < 180^0 & \text{then Stable '1'} \\ \text{if } \delta_{ij} \geq 180^0 & \text{then Ustable '0'} \end{array} \quad (7)$$

Where: δ_{ij} means the rotor angle deviation between any two generators during the transient period.

2. Data Generation

A large number of samples are generated through off-line simulation and the stable status is evaluated for each contingency under study. Data for each three-phase line fault occurring in the test systems are recorded in which samples of data are kept in a database. Each sample is characterized by a number of attributes such as load level, voltages, power generation,…To implement this application, proper training data should be prepared by detailed load flow and dynamic stability studies for different operating cases. A total of 270 samples were generated, which cover various load/generation patterns dividing equally into 10 levels from 50% to 140% basic load. Under the dynamic stability rules (7), there are 202 stable and 68 unstable samples, respectively. To comprehensively test the studied methods without loss of generality, k subsets cross validation [7] is employed: the database is randomly partition into k mutually exclusive subsets, D_1, D_2,…D_i,…,D_k, each equal size. Training and testing is performed k times. In iteration i, D_i is designated as the test set, while the remaining subsets are all combined and used for training. The validation accuracy is computed for each of the k validation sets, and averaged to get a final cross-validation accuracy. Four subsets are tested in this paper.

3. Input/Output variables

The input is the vector of system state parameters that characterize the current system state, usually called feature, they can be classified into pre-fault, fault-on and post-fault features. Pre-fault features [2]: steady-state operating parameters such as voltage magnitude and angle of buses, P, Q load, generation and line flow qualities P_{flow}, Q_{flow}, P_{load}, Q_{load}, V_{bus}, and before disturbance occurs (P_{gen}, Q_{gen}, δ_{bus},…). Post-fault features [2]: variables that describe system dynamic behavior after disturbance occur such as relative rotor angle, rotor angular velocity, rotor acceleration, rotor kinetic energy, and the dynamic voltage trajectory,… The use the post-fault variables can be too long for operators to take timely remedial actions to stop the extremely fast transient instability development process. Fault-on features[9]: variables that characterize at fault-on state of power system occur such as changes in nodal powers, in power flows in transmission line, voltage drops in the nodes at instance of fault (ΔP_{flow}, ΔQ_{flow}, ΔP_{load}, ΔQ_{load}, ΔV_{bus},…).

For the output, which is the parametric values representing the dynamic stability conditions, they can be classified into numerical and nominal categories [2]. The numerical output can indicate the continuous stability degree, so that the DSA will be a regression problem. Alternatively, nominal output can only represent the discrete stability status. So, the key question in dynamic stability assessment is the transient swings are finally stable or unstable [8].

With fault-on system operating conditions, we have used here the following inputs for the MLNF:

- Voltage drops of all buses: ΔV_{bus}.

- Changes in power flows in all transmission lines: ΔP_{flow}, ΔQ_{flow}.

-Changes in nodal powers of all the loads: ΔP_{load}, ΔQ_{load}. So, Input features are vector X[ΔV_{bus}, ΔP_{flow}, ΔQ_{flow}, ΔP_{load}, ΔQ_{load}], and Output is vector Y[Stable, Unstable]. For the IEEE 9-bus test system, the total number of input features is 33 (9 + 18 + 6). The number output is only one, Y [1,0].

After training of the MLFN, in the prediction phase, the single output feature of each MLFN usually has some error with respect to its actual binary value. This standard is also used in the interpreter to determine the output status of each MLFN [2],[5]

$$\begin{aligned} &\text{if } y_i \geq 0.8 \rightarrow y_i = 1\,(\text{Stable}) \\ &\text{if } y_i \leq 0.8 \rightarrow y_i = 0\,(\text{Unstable}) \end{aligned} \quad (8)$$

4. Normalization of data[9]:

Normalization is a method used to preprocess the input data before input them into the MLFN in which the data is constrained in terms of range of input features of a MLFN. Normalization of values of the features is carried out using formula:

$$z_i = \frac{x_i - m_i}{\sigma_i} \quad (9)$$

Where: m_i is mean value of data. σ_i is standard deviation of data.

5. Index Fisher calculation

The index Fisher F_s of every feature or variable is calculated on the training set using a feature selection program. Value of top features is arranged in descending order as Table 1.

Table1. Index Fisher calculation results

Feature	F_s	Feature	F_s	Feature	F_s
ΔQ_{41}	0.389	ΔV_2	0.149	ΔQ_{78}	0.104
ΔQ_{93}	0.257	ΔP_{27}	0.146	ΔP_{96}	0.078
ΔQ_{27}	0.181	ΔV_1	0.125	ΔV_3	0.072
ΔP_{75}	0.170	ΔP_{78}	0.107	ΔP_{93}	0.070

6. Training and classification performance

In the study, the results, all feature selection are tested, are given in Table 2.The testing results of the MLFN incorporating with and without CA and FD techniques are shown in Table 3.

Table 2. Classification Accuracy (%) with all features

Feature	Subset	Training		Testing
		%	Time(s)	%
33	1	99.0	2.11	91.2
	2	96.1	2.23	94.1
	3	94.1	2.27	94.1
	4	99.0	2.45	97.1
	Average	97.1	2.26	94.1

Table 2 shows the overall features to be used for the dynamic stability classifier using MLFN with average training classification accuracy 97,1% and average testing classification accuracy 94,1%.

The variables that have high index Fs have high separate data between two classes. Therefore, these variables were selected as input variables of training (Table 1). Subset Variables, reached accurate recognition of the expected value (^{3} 90%) [9], were selected (Table 3). In Table 3, there are 10 features as the input to the MLFN, average training classification accuracy 97.5% and the average testing classification accuracy 93.4%. When FD&CA method are employed, there are feature reduction for MLFN from 10 features to 8 features, average training classification accuracy 95.1% and the average testing classification accuracy 91.9%. This indicates that by applying CA method, 2 of the redundant input features are eliminated thus average training and testing accuracy still reached the expected value.

In terms of training times, the number of input features of the test system influences the time taken to train the MLFN. The time taken to train the MLFN is reduced when both FD and FD&CA are employed. It can be seen that the number of input features influences the training time of the MLFN.

VI. CONCLUSIONS

The performance of MLFN with feature selection for DSA of IEEE 9-bus power system has been presented in this paper. By employing FD and CA method for feature reduction, the number of features is reduced to 75% of the original features. However, the reduced features do not result in much decrease in accuracy of MLFN. The average classification accuracy testing of MLFN is reduced only 2.2%.This proves efficiency of DSA using MLFN with reduced feature selection methods. The result of classification accuracy has reached the expected value.

The training time of MLFN is slightly reduced when both FD and FD&CA are employed in reducing of the number of input features. Research is in progress in extending to dynamic stability assessment with larger diagram power system networks.

Table 3.Average Classification Accuracy (%) with FD, FD & CA method

Total Feature	FD				FD&CA			
	Training			Testing	Training			Testing
	Feature	%	Time(s)	%	Feature	%	Time(s)	%
33	10	97.5	2.14	93.4	8	95.1	1.92	91.9

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